Real Effects of Markets on Politics: Evidence from U.S. Presidential Elections

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Abstract

We explore the electoral implications of stock market fluctuations. Analyzing the outcome of presidential elections at the county level from 1992 to 2016, we find that the market return directly influences U.S. presidential elections, but with significant heterogeneous effects among constituents. Counties with high stock market participation are more likely to vote for the incumbent party when the stock market has performed well since the previous election relative to low participation counties. Our results are robust to controlling for various aggregate and local shocks and various model specifications. The effect of the stock market on voting is weaker in partisan and Republican leaning counties and in battleground states, and is not driven by differential voter turnout. Overall, our finding provides evidence on the effect of the stock market on politics and a novel channel through which stock market fluctuations could be transmitted into the real economy.

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1 Introduction

Politicians, the news media, and researchers often take it as given that the economy in general, and the stock market in particular, influence elections. This has tremendously important implications. If the economy impacts election outcomes, parties in power have incentives to manipulate macroeconomic policies to maximize the probability of reelection, resulting in what has been termed the political business cycle (Nordhaus, 1975, MacRae, 1977, Rogoff and Sibert, 1988) and potentially explaining consistently different economic policies across parties (Alesina, 1987), which could cause partisan return patterns (Santa-Clara and Valkanov, 2003, Belo, Gala, and Li, 2013, Blinder and Watson, 2016).

While "economic voting" (voting as a function of economic conditions) has been widely studied in the political science literature, there is strikingly little evidence on the impact of the stock market itself on voting patterns, and ultimately, on the political economy. In fact, the existing evidence supports a different direction of causality. Snowberg, Wolfers, and Zitzewitz (2007) show strong causal evidence that security market prices reflect expectations of election outcomes, consistent with research finding that government policies and regulation have a direct impact on corporations and stock prices (McGrattan and Prescott, 2005, Pastor and Veronesi, 2012, 2013, Belo and Yu, 2013). However, while the stock market may respond to expected outcomes, it can simultaneously impact them. In this paper, we document evidence that stock market returns impact voting outcomes.

Estimating stock market's influence on voting with aggregate data is challenging because of reverse causality and omitted variables concerns. To identify a causal effect of the stock market on voting, we focus on heterogeneity in the cross section. We hypothesize that if the market affects voting, then stock returns will have a stronger relation to voting among voters that participate in the stock market relative to those that do not. This is consistent with theory and evidence that voters are influenced by their personal financial interests and experiences, and voters' views about the incumbent president's performance with respect to the stock market's performance may very well depend on the share of the voter's income coming from labor versus capital.[1] Alternatively, if causation is solely in the opposite direc-

[1] Research supports the view that voters consider their own economic and financial interests (egotropic voting), or those of society as a whole (sociotropic voting), see e.g. Lewis-Beck and Stegmaier (2000), Singer and Carlin (2013). Furthermore, in a recent WSJ article titled, "Dont Bet on Trump Rescuing the Stock Market", the author posits that Trump may not back away from trade wars to rescue the stock market if

tion and the market is responding to expectations of election outcomes rather than causing them, then those voting outcomes should not vary cross-sectionally as a function of voters' exposure to the stock market.

Using county level variation in stock market participation, which we measure as the fraction of income coming from dividends, we find that recent stock returns relate more positively to incumbent vote shares in presidential elections in areas with higher stock participation. Our estimate shows that a one-percentage-point higher dividend income ratio is associated with an increase in incumbent vote share by 2.4 percentage points in response to a four-year stock market return of 99.6% (the difference between real stock market returns during 1997 – 2000 (85.8%) and 2005 – 2008 (-13.8%)).

We show that this result is robust to various model specifications, including controlling for local economic, demographic, and labor market conditions, allowing for these local economic and demographic factors to affect the sensitivity of voting outcomes to stock returns, adding state by year fixed effects, using an alternative measure of stock participation, and using instrumental variable estimation where local stock participation is instrumented using stock participation at the beginning of the sample period and local education level. We also show that the effect of the stock market is distinct from an interaction between stock participation and GDP growth, which does not load significantly in our estimation. These tests rule out the possibility that the market return is merely proxying for other economic channels to which counties may be disproportionately exposed. We also employ a comprehensive specification permutation analysis to examine the robustness of the findings to the inclusion of a large number of macro-variables, cross-sectional county characteristics, and sub-samples. Our evidence suggests the main results are not driven by omitted location characteristics or macro factors and are not sensitive to sample selection issues.

We show that the differential voting response to stock returns we document may very well affect which party wins a county, a state, and even ultimately, the presidency. To infer the aggregate effect of stock returns from our regional estimation, we need to make assumptions about the level effect, e.g., how counties with zero stock participation react to stock returns, controlling for other aggregate shocks.[2] If we assume that non-participants' votes do not

Trump thinks "electoral success rests more with bashing trade partners than supporting stocks."

[2]See Charles, Hurst, and Notowidigdo (2018) and Mian and Sufi (2011) for discussion of inferring the aggregate effect from regional estimations in the housing market setting.

vary with stock returns, a counterfactual exercise suggests that McCain would have won 175 more counties and the states of Florida, Indiana, North Carolina, and Ohio, if the market had produced returns in the four years leading up to the 2008 election similar to those that occurred during 1997–2000. In reality, the aggregate effect could be larger if, for example, even people who do not own stocks see the stock market as the incumbent party's report card, or smaller if, for example, high stock returns are associated with negative outcomes for non-participates (e.g., due to lower tariffs or lower corporate tax rates).

Our results provide evidence that the stock market influences election outcomes. We next examine variation in the effect to provide supporting evidence of the primary results, but also, and perhaps more importantly, to better understand the mechanism and identify situations in which the effect is mitigated. We examine if the effect is attenuated when more information about an election or candidate is available, i.e., when elections are pivotal or when voters have strong priors. We also test whether the saliency of the return as it relates to the candidate matters by examining differences in timing of returns and comparing overall market returns to returns based on local industries. Finally, we explore the relation between market returns and voter turnout.

In the cross section, we find that the effect is smaller in partisan and Republican leaning counties. One interpretation is that voters in these counties tend to have strong priors about political and economic issues, and market returns are less likely to shift voters from their priors. We also find that the effect is weaker in politically active counties, i.e. those located in swing states. These counties are generally exposed to more information flows due to additional campaigning, potentially mitigating the impact of market information.

We also examine potential differences in the importance of various returns. To examine the timing of market returns, we separate the cumulative market return into four annual returns, one for each year leading up to the election. We find that returns during the incumbent's first year in office, and the returns occurring right before the election are the most important. However, none of the single year return interactions with participation remains statistically significant after controlling for the total four-year return. Thus it appears that what matters for voters' decisions is indeed the cumulative stock market performance since the last election.

To examine if certain industries' or stocks' returns matter more than others, or more than

the market return in aggregate, we include returns of the industries that tend to employ the constituents of the county. We then compare the effect of market returns to that of these "local" stock returns. Perhaps surprisingly, the returns of the industries most closely associated with the county do not affect voting, after controlling for the effect of aggregate returns. This is consistent with the view that voters relate market-wide returns to the national office. This finding has significant implications for the political business cycle in that presidential incumbent parties have an incentive to influence overall market returns, rather than a subset of specific industries, in order to sway voters through the stock market's impact shown in this paper.

Last, to explore the extensive margin we estimate an effect of market returns on voter turnout. We find a slight decline in voter turnout in high participation counties following good stock returns, relative to low participation counties. Moreover, the main effect on vote share does not vary with changes in voter turnout, suggesting that the effect is mostly coming from the intensive margin, i.e., party switching of existing voters.

Our findings contribute to the literature in several ways. First, the paper shows a new real effect of the stock market. Stock market performance is not always in sync with real economic activities and is subject to "animal spirits" and has large swings. The evidence in this paper, on top of the political business cycle literature, suggests a novel political channel of stock market influence, whereby the stock market performance could feed back into the real economy by influencing political leaders and policies. Existing literature has shown the important effect of politics on stock returns (Santa-Clara and Valkanov (2003), Snowberg et al. (2007), and Pastor and Veronesi (2017)). We instead look at the other direction. For example, in the model of Pastor and Veronesi (2017), an increase in risk aversion leads to higher expected stock returns and greater probability of Democrats being elected. Our finding suggests a certain degree of path dependence — realized stock returns due to changes in risk aversion could benefit either Democrats or Republican depending on which party is in power at the time.

Second, this paper adds to the large literature on economic voting by showing that not only the overall economic growth, but also personal exposure and the distribution of wealth, matter for election outcomes. Government policies such as taxes and regulation not only affect overall economic growth but also wealth distribution, for example, between

capital owners and wage earners. Despite its obvious relevance, existing studies of economic determinants of electoral outcomes rarely examine the distribution of income and wealth, and instead focus on the aggregate economic output. As stated by Stigler (1973), "One should not infer that economic questions are unimportant to the policies of parties or to the various groups in the population who systematically support one of the parties. There are a host of distributional policies which are inescapably divisive ... The economic bases for party affiliation must be sought in this area of income redistribution."

Third, this paper highlights the political effect of stock market participation. It has been argued that participation is too low due to various frictions.[3] Figure 1 shows direct stock participation increased steadily in the 1990s and since then has dramatically declined over the past two decades.[4] Ljungqvist, Persson, and Tag (2018) develop a political economy model to show that the decline in the number of listed firms and stock market participation in the U.S. reduces citizen-investors' exposure to corporate profits and undermine popular support for business-friendly policies. Our evidence suggests that citizen-investors learn from stock market performance to judge the policies of the incumbent party, and variation in aggregation participation would affect the sensitivity of election outcomes to stock market performance.[5] In this regard, this paper also echoes the findings in recent literature on individual financial asset ownership and political attitude in historical settings. Jha (2015) finds that people owning shares in overseas joint stock companies is associated with greater support reform and institutionalization of parliamentary supremacy over dictatorial rule during England's Civil War (1642-1648). Hilt and Rahn (2018) find that owning liberty bonds by American households during World War I increased voters' sensitivity to financial assets and voters held incumbent accountable for the fluctuations in bond prices, which led

[3]In a recent WSJ commentary, citing that mere wage earners are missing out the stock market boom, the author urges the congress to "consider a revamped version of this ["baby bond"] initiative that offers future American the opportunity to become stockholding capitalists" (David Smick, *America Needs Federal 'baby bonds'*, April 26, 2018, WSJ)

[4]Even after taking into account stock market investment through retirement plans, stock ownership is still lower than 20 years ago, according to a recent Gallup poll, `https://news.gallup.com/poll/233747/stock-ownership-among-americans-trends.aspx`.

[5]In related literature, Bonaparte and Kumar (2013) find that political activism increases people's propensity to participate in the stock market, and Kaustia and Torstila (2011) find that left-wing voters and politicians are less likely to invest in stocks. Our paper complements these studies by showing that while people with different political beliefs may have different propensity to invest in stocks, investment in stocks could also shape people's beliefs and votes for different political parties. Kaustia, Knpfer, and Torstila (2016) find that greater stock ownership increases the vote share for right-wing parties that are seen as more stock market friendly.

to voting against the Democratic Party in the 1920 and 1924 presidential elections. Finally, using a field experiment in Israel prior to the 2015 election, Jha and Shayo (2019) find financial market exposure through financial asset ownership shifted voter choices towards parties more supportive of the peace process.

2 Literature review

2.1 Economic voting

There is a long literature in political science and economics examining how economic conditions affect voting.[6] Some of the most influential studies, such as Kramer (1971) and Fair (1978), analyze how national-level (macro) economic conditions affect votes for the incumbent presidents and their parties. In general, this literature concludes that, at least in the U.S., positive economic performance rewards the incumbent party and improves their re-election prospects.[7]

The studies using macro-level data, while simple and straightforward, are limited by the size of the sample and the number of independent variables that can be included in the estimation. As a result, they cannot test many potential economic variables of interest, or discriminate among these variables such as economic growth, income, employment, etc. Therefore, it is not surprising that stock market performance has so far been omitted in these time-series studies even though it is frequently discussed by politicians and the popular press as an indicator of the the incumbent's performance.[8]

Another limitation of focusing on national-level economic conditions is that overall economic conditions fail to take into account how output is distributed. Examining aggregate economic growth might obscure the identification of effects if voters have heterogeneous exposure to political policies. Political parties often have different redistributive and regu-

[6]See Lewis-Beck and Stegmaier (2000) for a comprehensive review of the literature, and Anderson (2007) for a critical assessment of the theory and empirics of economic voting.

[7]The economic voting channel appears to be less important in other countries. See Brender and Drazen (2008) for a discussion of the literature.

[8]President Trump has talked or tweeted about the stock market numerous times since inauguration. See an interesting interactive graphic from Thomas Reuters, http://fingfx.thomsonreuters.com/gfx/rngs/STOCKS-USA-TRUMP/010051M43MT/index.html. The Treasury Secretary Steven Mnuchin believes that the stock market serves as the Trump administration's economic report card https://www.cnbc.com/2017/02/23/mnuchin-the-stock-market-is-the-trump-administrations-report-card.html

latory policies that could impact individual voters differently based on their socio-economic status, condition of employment, location, etc. Lewis-Beck and Stegmaier (2000) conclude that "This work, and actually almost all extant economic voting research, assumes the most relevant evaluation dimension is global economic output, i.e. "How is the nation's economy doing?" But economic distribution may be an emerging relevant dimension. That is, what are the electoral effects of rising income inequality and insecurity? We can cite no published scientific paper on that exciting question." Using the terms in Lewis-Beck and Stegmaier (2000), these distributional effects are important if voters are pocketbook voters who judge the incumbent by their own personal economic conditions.

The economic voting literature also debates the relative importance of the retrospective versus prospective economic evaluations (Lewis-Beck and Stegmaier (2000)). In this regard, stock market performance also differs from other macroeconomic factors in that it is forward looking and thus is a useful indicator for prospective voters to evaluate the incumbent president's policies that have yet to be reflected in real economic activities.

2.2 Political business cycles

The potential impact of markets on politics, though interesting in its own right, would not matter for the real economy if politicians were agents who react passively to economic shocks with a fixed set of rules. However, there is strong theoretical and empirical evidence to suggest that this is not the case. To the extent that voters believe that politicians matter for economic outcomes, politicians have incentives to engage in pre-electoral manipulation to boost short-term economic performance and increase the probability of reelection. This will give rise to the so called political business cycles, pioneered by Nordhaus (1975) and MacRae (1977), who assume voters are myopic. This early research on political business cycles was later extended to accommodate more rational, forward-looking voters. Rogoff and Sibert (1988) show that political business cycles could still exist even when voters are rational but there is information asymmetry between voters and the incumbent party regarding the "competency" of the incumbent. Alesina (1987) assumes that parties have different objectives and incentives and shows that different parties adopt different policies in equilibrium, giving rise to the partisan view of macroeconomic policy. The fiscal policies adopted by political parties to maximize their objective function and the uncertainty of these policies

can then be transmitted to financial markets (Belo and Yu (2013), Belo et al. (2013), Pastor and Veronesi (2012), and Pastor and Veronesi (2013)).

Snowberg et al. (2007) find that equity valuations raise by 2 to 3 percent in anticipation of a Republican president. They interpret their finding of higher equity values under Bush to be consistent with "expectations of favored treatment of capital over labor, current firms over future entrants, equity over bond holders, or expectations of stronger real activity." Santa-Clara and Valkanov (2003), on the other hand, show that the stock market returns are much higher under Democratic presidents than Republican presidents. Our finding suggests that voters do not always view any one party to be good for the stock market. Instead, their beliefs are very much shaped by personal experience. Pastor and Veronesi (2017) treat incumbents and challengers symmetrically but suggest that their model could be extended to incorporate the incumbent-challenger asymmetry, which is what we show in this paper.

2.3 Real effects of stock markets

The stock market is not just a passive predictor of future economic activities — it influences and is influenced by the real economy. Markets fluctuate for reasons not necessarily related to economic fundamentals and market performance can feed back into the real economy in many ways. The neoclassical theory (Q-theory) of investment predicts a direct effect of equity valuation on firm investment. The fluctuation in valuation could be caused by changes in fundamentals, as well as investor risk premium and sentiment. Inspired by the debate in the 1980s on market efficiency, an influential literature examines whether the stock market is just a sideshow and to what extent it influences firm investment and the real economy (Morck, Shleifer, and Vishny (1990), Blanchard, Rhee, and Summers (1993), Stein (1989), and Bond, Edmans, and Goldstein (2012)). In addition to the potential direct influence on the behavior of publicly traded firms, market valuation could also affect household consumption through a wealth effect (Poterba (2000)), and bank dependent firms through a deposit channel (Lin (2019)).

The literature on the real effects of the stock market has not examined the potential role played by politics, despite that new media and politicians frequently mention stock market performance as a vote of confidence for the president's economic policies. To the extent politics influences the real economy through fiscal policy and regulation, as discussed

above, stock market performance could also be transmitted into the real economy through its impact on election outcomes.

3 Data and summary statistics

3.1 County stock market participation

Our unit of analysis is at the county level. To measure a county's stock market participation, we use the ratio of its aggregate dividend income over adjusted gross income. The breakdown of taxable income at the county level is from the IRS (https://www.irs.gov/uac/soi-tax-stats-county-data). The data are available from 1989 through 2016. The IRS data have been used to measure local stock market exposure by Lin (2019) and Chodorow-Reich, Nenov, and Simsek (2019). One advantage of the IRS data is that the data cover all households that file tax returns, which allows for measuring of stock market participation at a very granular level. For the purpose of this paper, one drawback of the dividend measure of stock market participation is that it does not capture exposure to the stock market through nontaxable accounts such as retirement plans. Moreover, as pointed out by Lin (2019), there are several measurement error issues with using dividend income to measure stock market participation. One potential measurement error is due to the dividend clientele effect—if households in certain areas tend to invest more in dividend-paying stocks, the dividend income ratio will tend to overestimate the stock market participation of these households relative to households in other areas. The other is that dividends received by households are not all paid out by publicly traded companies. To the extent that the measurement error in participation is not correlated with the sensitivity of voting to stock market performance after controlling for potentially different sensitivity due to income, age, race, etc., our point estimate could be biased downwards because of the measurement error in stock market exposure. We also show that our results are robust to using a binary measure of participation: whether or not a tax return reports any taxable dividend income.

Table 1 shows that, on average, dividend income accounts for 1.6% of total income, with substantial variation across counties. Figure 2 shows the dividend income ratios across U.S. counties in 1989 and 2016. The degree of stock participation as measured by the dividend income ratio appears to be highly persistent at the county level. This visual impression is

confirmed by the test below that shows that dividend income ratio in 1989 alone can explain half of the variation in dividend income ratios.

3.2 Election data

We obtain presidential election data at the county level from CQ Voting and Elections Collection. It reports the number of votes for Democratic, Republic, and third party candidates. Because the county stock market participation data start in 1989, we examine the election results from 1992 to 2016, a total of 7 elections. Figure 3 shows the vote share for the Republican candidates in 1996 (Bob Dole) and 2016 (Donald Trump). While there is obvious persistence in county voting patterns over time, many more counties were won by Donald Trump than Bob Dole 20 years ago. To filter out the persistency in county's leaning toward one party, our main dependent variable will be the change in the vote share for the incumbent party from the previous to the current election. Table 1 shows that, on average, the incumbent party wins 44.3% of the total votes at the county level. The average vote share for Democratic candidates is lower than that for Republican candidates despite the fact that the Democratic party won 4 out of the 7 recent elections, reflecting the fact that Republican candidates tend to win smaller counties.

3.3 Stock returns

We obtain monthly returns of the value-weighted stock index from the Center for Research in Security Prices (CRSP). We compute the real cumulative returns over a four year window from November of the previous election year to October of the current election year. We include the November return during the previous election because of the anticipation effect—the market moves in anticipation of any changes in fiscal policies and regulations after the election, but before the new president takes office. For example, U.S. stocks surged by more than one percent on the Wednesday after Donald Trump was elected (despite a sharp plunge in stock index futures overnight), and continued to rise before Trump took office, potentially due to the market's expectation that lower corporate rates and reduced regulation could boost corporate profits. Therefore, for each presidential term, we include returns from the previous election to inauguration as part of the cumulative return during incumbency.

However, our estimates change little if we use returns that begin only at inauguration in our calculation of cumulative returns between elections. Table 1 shows that the average real four-year returns is 36.4%, ranging from -18.9% from 2000 to 2004 and -13.8% from 2004 to 2008 to 63.9% from 1992 to 1996 and 85.8% from 1996 to 2000.

3.4 Other county level data

We obtain annual income per capita and total population data at the county level from the Bureau of Economic Analysis. We obtain county level unemployment rate from the Bureau of Labor Statistics (BLS), and the annual average wages from BLS's Quarterly Census of Employment and Wages (QCEW). County population data by age and race from 1990 to 2016 are obtained from the Census Population and Housing Unit Estimates Datasets (https://www.census.gov/programs-surveys/popest/data/data-sets.html). For each election from 1996 to 2016 we use the age and race data recorded since last election as controls. For the 1992 election, we use the 1990 age and race data because the county population data by age and race are not available before 1990. Since we do not have county level data on the number of eligible voters, we define voter turnout as the number of votes in a county divided by the county population aged 20 or above, as in Charles and Stephens (2013). By this definition, both the mean and median voter turnout is around 58.4%, which is higher than the actual voter turnout by construction. We obtain educational attainment in 1990 (percent of people 25 years or older who have a bachelor degree or higher) from Census Bureau's 1990 Census.

3.5 Other aggregate data

We obtain quarterly aggregate earnings and unemployment data from the Bureau of Labor Statistics, real median household income data form the Census Bureau, real GDP per capita from the Bureau of Economic Analysis, S&P/Case-Shiller U.S. National Home Price from S&P Dow Jones Indices, and the credit spread index from Gilchrist and Zakrajsek (2012).

4 Empirical results

4.1 Methodology

Some of the most influential studies on economic voting, such as Fair (1978), use aggregate time series data. However, the small number of presidential elections limits the number of economic variables and controls that can be examined at the same time. Therefore, it is challenging to make causal interpretations of these results due to potential omitted variable concerns. For our test, we rely on the regional variation in voters' personal exposure to the stock market to detect the effect of the stock market on voting and to establish a causal link between the two. The identification assumption is that any potential omitted variables (after controlling for GDP growth and other observed macro variables) do not have the same heterogenous effect as the recent stock market performance on the behavior of voters with different stock market participation (after controlling for income and other county-level observables).

Specifically, we estimate the following model,

$$\begin{aligned}\Delta Incum_{i,t} =& \alpha_t + \beta_1 Div\_ratio_{i,t-4} \times ret_{[t-4,t-1]} + \beta_2 Div\_ratio_{i,t-4} + \beta_3 X_{i,t-4} \times ret_{[t-4,t-1]} \\ &+ \beta_4 \Delta X_{i,t} + \beta_5 \Delta X_{i,t} \times DemIncum + \beta_6 Div\_ratio_{i,t-4} \times Aggre_{[t-4,t-1]} + \epsilon_{i,t}\end{aligned} \tag{1}$$

where the dependent variable is the change in vote share for the incumbent party in county i in election year t. In 1996, 2000, 2012, and 2016, the dependent variable is the difference in vote share for the Democratic party between the last and current election, and in 1992, 2004, and 2008, the dependent variable is the difference in vote share for the Republican party between the last and current election. This model takes into account the persistence in voting for a given party at the county level, and can be seen as a multi-year version of the model used in Antoniades and Calomiris (2018) (Eq. (2), Page 20). Div_ratio is the dividend income ratio measured during the last election year. $ret_{[t-4,t-1]}$ is the cumulative stock returns from November of the previous election year to October of the current election year. To account for shocks to local economic conditions unrelated to county stock market exposure, we control for the growth of county income per capita and county population,

the change in county unemployment rate, and the growth of average wages. To account for changes in local demographics that could be correlated with shifts in votes for a given party, we control for changes in the fraction of the population that is White, Hispanic, and Black, the fraction of the population that is under 20 or over 65. We also allow the effect of the change in local economic and demographic variables to vary with the identity of the incumbent party by including their interactions with an indicator variable, $DemIncum$, equal to one if the incumbent party is the Democratic party and -1 otherwise. For example, if an increase in the share of Black population in a county tends to increase the county's votes share for the Democratic Party, the interaction term between changes in Black population share and $DemIncum$ would be positive.

With all these controls, one may remain concerned about omitted variables that are correlated with both our stock participation measure and the sensitivity of a county's vote share for the incumbent party to the stock market performance. We extend our baseline specification in several ways to alleviate such concerns. First, we allow the sensitivity of vote share to stock return to vary with other county characteristics such as income per capita, population, and county demographic variables. Second, we use a county's dividend income ratio and education level at the beginning of the sample period as instrument variables for dividend income ratio in later years, which should alleviate concerns about biases due to reserve causality or omitted time-varying county variables. Lastly, to show that the effect of stock returns is distinct as opposed to simply being a sideshow of other real economic outcomes, in some specifications we also control for interactions between dividend income ratio and a slew of other aggregate shocks during the four-year period, including GDP growth, change in median household income, change in aggregate unemployment rate, growth in real income per capita. In subsection 4.2.7, we employ a comprehensive specification permutation analysis to further examine the robustness of the findings to the inclusion of a large number of macro-variables, cross-sectional county characteristics, and sub-samples.

4.2 Stock market performance and votes for the incumbent party candidate

4.2.1 Baseline results

We begin with a simple univariate analysis and examine how incumbent vote shares vary with local stock market participation and recent stock market performance. We sort counties by dividend income ratio into ten groups. For each group, we calculate the average change in incumbent vote share in the 2000 election when the stock market had more than doubled in nominal value since the last election and in 2008 when the stock market value was actually lower than four years prior due to the financial crisis. Figure 4 reveals striking patterns in the voting behavior of the ten groups in the two elections. In 2000, higher participation counties are more likely to increase their votes for the incumbent party (Democratic), with the difference between the bottom and top decile of about 2 percentage points. In 2008, the pattern is reversed: on average, the highest participation group reduces their support for the Republican party by almost 5 percentage points, compared to almost no change for the lowest participation counties.[9]

We next show that the pattern observed in the 2000 and 2008 elections generalizes to other elections in our sample by estimating the sensitivity of vote share to stock returns for each dividend income decile. Specifically, for counties in each decile of dividend income ratio j, we regress the change in incumbent vote share on stock return,

$$\Delta Incum_{ijt} = \alpha_j + \beta_j ret_t + \epsilon_{ijt}, \tag{2}$$

where i indicates county, and $\Delta Incum_{ijt}$ is demeaned by its annual average across all counties. Figure 5 plots the estimated coefficient of stock return for each dividend income decile, as well as the 90% confidence intervals based on standard errors clustered by year. It shows that counties with high dividend income ratios reward the incumbent party more following good returns and the sensitivity increases almost linearly with dividend income ratios.

We now examine this effect more systematically by estimating Eq. (1). Table 2 reports

[9]Despite the exceptional stock market performance from 1996 to 2000, the Democratic Party lost in the 2000 presidential election. However, there are obviously many other factors that influence the outcome of a particular election, which is precisely why we focus on the cross-sectional variation in vote shares.

the results. Column (1) presents the estimated effect without year fixed effects or any county controls. The interaction term is significantly positive, suggesting that counties with high participation are more likely to vote for the incumbent relative to the previous election if the stock market has performed well since the last election. The main effect of the market return is imprecisely estimated and not statistically significant at any level of participation. In column (2), we include year fixed effects, which raise the coefficient of the interaction term to 2.29. Column (3) adds county economic and demographic controls, further raising the point estimate to 2.43. This point estimate implies that, relative to a low cumulative stock return of -13.8% (2004-2008), a high cumulative return of 85.8% (1996-2000) leads to an increase of about 2.4 percentage points in the incumbent vote share for each one-percentage-point increase in dividend income ratio.

To more directly examine if the stock market is economically meaningful enough to affect whether the incumbent party wins or loses a county, we replace the dependent variable with an indicator variable reflecting majority/minority changes in vote shares. Specifically, column (4) reports results using a dependent variable equal to 1 if the incumbent party's two-party vote share is less than 50% in the last election and more than 50% in this election (lose to win), -1 vice versa (win to lose), and 0 otherwise. The interaction term is positive and statistically significant, indicating that when the stock market has performed well recently, the incumbent party is more likely to "win over" counties with high stock market participation, and vice versa.

4.2.2 Extending the baseline specification

We next extend our baseline model in several ways. First, we estimate the regression where counties are weighted by their total population. The point estimate of 2.29, reported in column (1) of Panel B of 2, is slightly smaller but fairly close the unweighted estimate, which alleviates concerns about model misspecification as a result of failing to account for any heterogenous effects across counties of different sizes (Solon, Haider, and Wooldridge (2015)).

One concern about the results presented so far is that stock market participation could be correlated with other factors that might also cause counties to vote differently in response to recent stock market performance. To partially address this concern, we allow the sensi-

tivity of vote shares to stock return to vary with county size and wealth, and other county characteristics by including the interactions between stock returns and log population, income per capita, and other county demographic variables. Column (2) of Panel B reports the results. The coefficient of the interaction between stock returns and stock participation drops to 1.69. Not shown in the table, the interaction between log income per capital and stock return and the interaction between population and stock return are also significantly positive. Thus it appears that some of the effect of stock participation is picked up by income per capita and county size, both of which are positively correlated with participation. It is possible that the high income counties' greater sensitivity to the stock market could also be partially due to their higher equity exposure, not entirely captured by our participation measure. For example, wealthy individuals maybe be able to avoid paying taxes on certain equity distributions, in which case such distributions will not show up as taxable dividends in the IRS data.

Our next specification includes state by year fixed effects so that we are comparing counties within the same state in a given year. These fixed effects will wipe out any shocks common at the state level and thus will help address concerns about potentially confounding state-level shocks that are correlated with both voting outcomes and stock participation. We see that even within the same state, counties with greater stock exposure are more likely to reward the incumbent party during stock market booms.

4.2.3 IV estimation

To further address concerns about county omitted variables biasing the results, we conduct IV estimations using two instruments: county dividend income ratio in 1989 (first year the data is available) and education level as of 1990 (from the 1990 Census). Because the dependent variable is the *change* in vote share, using participation and education prior to the beginning of the sample period helps minimize the possibility that the exclusion condition is violated because of reverse causality or omitted time-varying county characteristics. For example, while education level could be correlated with voters' party affiliation (e.g., Marshall (2019)), it is less likely to directly affect the change in county vote share. The exclusion condition, however, can be violated if education is correlated with omitted county characteristics that cause counties to have different sensitivity to stock market returns other than

through stock market participation. We partially address this concern by again controlling for the interaction of county variables including income level with stock returns. We also continue to control for state by year fixed effects but note that the point estimates are similar if we do not control for them.

Panel C of Table 2 reports the results where we use 1989 dividend income ratio and 1990 education as instruments for dividend income ratio and their interaction with stock returns as an instrument for the interaction between dividend income ratio and stock returns, respectively.[10] The coefficient of $Div\_ratio \times ret$ using 1989 dividend income ratio as the IV is very close to the OLS result (column (3) of Panel B). When 1990 education level is used as the IV, the point estimate raises substantially to 4.87.

4.2.4 Other aggregate shocks

Our last extension to the baseline model aims to address the concerns about omitted aggregate variables. For example, an alternative explanation of our findings is that stock market performance is positively correlated with overall economic conditions and people with stock market exposure are more responsive to the aggregate economic output. In other words, it could be the case that individuals participating in the stock market are also those who benefit the most when the economy is expanding, due to reasons unrelated to their stock market exposure. If that is the case, we would expect that high participation counties are more likely to vote for the incumbent party when the economy has performed well recently, and the effect of stock market performance may be insignificant once recent GDP growth and other measures of economic conditions are considered. Column (1) of Table 3 shows that the estimate of stock market's influence actually becomes larger when allowing the sensitivity of vote share to GDP growth to vary with stock participation and other county controls. We perform similar tests for a host of other aggregate shocks between elections including changes in real wages, unemployment rate, federal funds rates, median household income, GDP per capita, house prices, and credit spread. The point estimate of stock market's influence varies somewhat across model specifications, but remain statistically significant at the 1% level in almost all specifications.

[10]The first-stage results are reported in Appendix Table A.I.

4.2.5 Aggregate effect

We could also use the point estimates to conduct a counterfactual exercise as in Antoniades and Calomiris (2018): how much would the electoral result have changed if the stock market had performed differently in the years before an election? For example, had the real stock return from 2004 to 2008 (-13.8%) been the same as what it was from 1996 to 2000 (85.8%), would the counterfactual voting difference at the county level be large enough to result in voting outcomes at the state or even the national level?

For this exercise, we use the relatively conservative point estimate of 1.69 from column (2) of Panel B of Table 2, and we add $1.69 \times (85.8\% - (-13.8\%)) \times Div\_ratio_i$ to the incumbent party (Republican) vote share for each county i and aggregate the total counterfactual votes to the state level. The exercise suggests that McCain would have won 176 more counties in this alternative world, which could lead him to win over the state of Florida, Indiana, North Carolina, and Ohio. These four states had a combined electoral vote of 73, which was not enough to make McCain win the election given Obama's landslide victory in 2008 but would be enough to change the election outcome for certain elections.

This rough calculation of the aggregate effect is clearly subject to various caveats and relies on important assumptions. It ignores the effect on vote shares of any aggregate shocks that affect stock returns or any general equilibrium effect of stock returns. Implicit in the calculation of the counterfactual effect is the assumption that vote shares in counties where nobody participates in the stock market (a dividend income ratio of 0) do not change when stock returns vary (holding constant other observed aggregate shocks). In reality, non-participants' votes for the incumbent party could respond either positively or negatively to a stock boom, depending on, for example, the cause of such a boom.

4.2.6 Binary measure of participation

To address potential measurement error concerns about county stock participation discussed in the data section, we alternatively measure a county's participation by the fraction of tax returns that report dividend income. Such a measure treats all people with exposure to the stock market equally regardless of their actual investment in the stock market. This is also an imperfect measure of stock participation. But to the extent that this alternative measure does not share the same sources of measurement errors, showing the robustness of

the results to this measure mitigates concerns about measurement errors driving our main results. Column (1) of Table 4 reports the results, which are consistent with what we find when using dividend income ratio to proxy for stock market participation.

In column (2), we include both the binary participation measure and dividend ratio in the same estimation. The tests of both interaction terms have low power, due to a combination of high correlation between the two participation measures and measurement errors in both measures. In the meantime, the binary participation interaction is statistically significant at the 10% level while the dividend ratio interaction term is not statistically significant. One interpretation of the results is that voters' actual exposure does not matter once we control for participation and thus the evidence could be viewed as being consistent with sociotropic voting and investor-voters are more likely to view the stock market performance as the incumbent party's report card. However, given the errors in using IRS dividend data to measure both participation and the actual exposure, we only view this evidence as being suggestive.

4.2.7 Comprehensive Specification Analysis

Our primary results are based on a relatively simple empirical strategy that compares voting outcomes differentially across counties with different market participation rates in periods of different market performance, a difference-in-difference-in-difference. As discussed in the prior sections, there are essentially three alternative explanations with which one may naturally be concerned. First, our empirical tests utilize variation from seven events. While this is more events than what is used in many dif-in-dif analyses, a concern is that our results are driven by our particular sample of elections (or a single election among them), or a subset of counties. Second, it is possible that stock market performance is proxying for other macro economic variation. We present what we view as the most natural specifications designed to control for other macro variables that are correlated with the market performance (e.g., GDP) in Table 3, but this does not consider many possible variant specifications. Third, it is possible that our measure of stock market participation is proxying for some other county level characteristic and it is the interaction of market performance with that characteristic that matters. Again, while we present select specifications designed to address this issue above in Table 2, in this section we address these three concerns comprehensively across

controls, alternative proxies, and samples in this section. We systematically evaluate all of these alternative explanations for our results using a permutation-based approach following Simonsohn, Simmons, and Nelson (2015).

We estimate the incumbent vote share as a function of market returns and stock market participation using a randomly chosen sample and specification. We repeat this one thousand times, and analyze the resulting series of coefficients of interest. The size of the sample in terms of elections used is randomly determined. Specifically we randomly drop elections from our sample, where each election is equally likely to be dropped, and we randomly choose to drop either two, one, or no elections. At each iteration, we also randomly select 75% of the counties. The control variables included in each regression are also randomized. In particular, we also include a randomly chosen alternative interaction control variable, varying either the macro variable (instead of the market return) or the cross-sectional variable (instead of participation) with equal probability. The alternative macro variables are: change in aggregate wages, change in federal funds rate, household income growth, GDP growth, GDP per capita growth, aggregate house price growth, and change in credit spread. The alternative cross-sectional varaibles are: income per capita (level and log), population (level and log), county unemployment rate, Caucasian population (level and ratio), black population (level and ratio), Hispanic population (level and ratio), population under 20 years old (level and ratio), population above 65 years old (level and ratio), and percent of county population that is located in an urban area.

We then estimate the coefficient on $Div\_ratio \times Return$ for each of the one thousand permutations and present the results in Figure 6. The coefficients are sorted by magnitude, and presented in order with the smallest estimated relationship on the left to highest on the right. The median estimate is 2.3, which is similar to many estimates throughout our paper. Out of all one thousand estimates, 997 are positive and only three are negative.

To compare these findings to what is expected under the null, we randomly assign stock market participation to counties and then repeat the permutation approach described above which generates 1,000 estimates. Finally, we repeat this process 500 times, each time reshuffling stock market participation across counties and estimating 1,000 coefficients. Randomly assigning stock market participation constructs the distribution under the null, and requires no assumptions regarding dependence. Instead, we only assume that participation is ex-

changeable, i.e., any county could have the participation of any other county.

We can use these bootstrapped estimates constructed under the null to test the significance of any given estimate, or of the estimates jointly. Regarding the significance of individual estimates, of our 1,000 coefficients estimated using the actual data, we find that one is negative and significant, two are insignificant, and 997 are positive and significant. Regarding the joint significance implied by the entire specification curve, we follow Simonsohn et al. (2015) and compare the fraction of estimates with a positive sign among the actual data to that in the bootstrapped samples. Among the 500 runs of 1,000 bootstrapped estimates, only 11 have at least 997 positive estimates. This produces a p-value of 0.022 for the joint significance test. In general, these results provide strong support for the view that our findings are robust to various specification and sampling choices.

While our evidence overwhelmingly indicates that the effect is positive and significant, it may still be useful to understand which, if any, choices affect estimated magnitudes. At the bottom of Figure 6 we plot the characteristics of each specification. The first seven rows report instances in which that year's election was dropped from the sample. There are no easily discernible patterns - results are not highly sensitive to which elections are included in the sample. The bottom two rows indicate instances in which certain interaction controls were included. Here there are easily identifiable patterns. Including a control for the interaction between Div_ratio and a randomly selected macro-economic variable produces estimates of lower magnitudes. However, these magnitudes are still larger on average (2.01) than the estimate from the simplest specification presented in column (1) of Table 2 (1.41). Controlling for an interaction between stock returns and a randomly selected county-level variable tends to produce estimates of higher magnitudes, in particular higher than the baseline specification. This suggests that important differences across counties may actually be biasing the coefficients downward. No matter which additional interactions are included, the main effect is statistically and economically important.

5 Additional Results

In this section we explore the conditional nature of the main result documented above. In particular, we examine if the effect varies with county-level characteristics such as parti-

sanship and ideology, if the timing of market returns matters, whether the returns of local stocks matter in addition to the market, and the extent to which the effect is through the intensive or extensive margins.

5.1 County Characteristics

We begin by examining whether the effect of stock returns varies with county-level partisanship and ideology. One might expect economic voting to be less important in highly partisan counties, because people in these counties tend to identify strongly with one party and thus are thus less likely to be retrospective economic voters, or they might have biased assessments of current and expected future economic performance (Gerber and Huber (2009) and Mian, Sufi, and Khoshkhou (2017)). There is also evidence that voter evaluation of government policy varies with ideology (i.e., conservative vs liberal. See, e.g., Kriner and Reeves (2012)).

We start by estimating the effect of the main interaction term within subsets of counties sorted by a measure of ideology, the average Democratic vote share. Figure 7 plots the point estimates of the main interaction term by decile of county Democratic vote share. Except for the top decile counties, the point estimate is statistically significant in all groups and varies between 1 to 3. There are two patterns that are noticeable. First, it appears that the effect is stronger among more Democratic leaning counties. Second, the effect appears to be weaker in strongly partisan counties (bottom two deciles and top decile). This visual evidence is consistent with the results shown in the first four columns of Panel A of Table 5, where we split counties by partisanship, whereby partisan counties are those in the top and bottom decile of average Democratic share of the two-party vote, and the tendency to vote for the Democratic party. The effect is larger in less partisan and more Democratic leaning counties.

We next examine whether the effect we document varies with political activeness. Greater political engagement is generally associated with greater media consumption and political knowledge, which could influence the strength of the economic voting channel (Alt, Lassen, and Marshall (2016)) or the informational value of stock market performance. We proxy for political activeness by whether a county is located in a swing state and by lagged voter turnout. In particular, counties are considered to be politically active if they are located in swing states (Kriner and Reeves (2012) and Bonaparte and Kumar (2013)) or they have

above-median voter turnout. Our list of swing states include Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, Virginia, and Wisconsin. The last four columns show that the effect is indeed stronger in less political active areas—in non-battle-ground states and in counties with lower turnout.

In Panel B, we evaluate the relative strength and statistical significance of these heterogeneities by including the triple interactions of dividend ratio and stock return and one of the conditional variables (all the double interactions are also included but not reported in the table). Column (1) shows that only the triple interaction with Democratic leaning indicator is statistically significant. In Column (2), we further allow year fixed effects to vary with the conditional variables. The effect of ideology remains statistically significant and the effect is also significantly weaker in swing states. One possible explanation is again that the economic voting channel might be weaker when voters are more political active because they tend to feel strongly about other issues. Another possibility is that politically active voters do not rely on stock market performance as much to evaluate the performance of presidents, which leads to smaller difference in the sensitivity of voting behavior to stock market performance between stock market participants and non-participants.

5.2 The Timing of Stock Returns

We next examine the effect of stock returns of individual years since the last election. This exercise will allow us to see whether the effects are driven by any single year during the past four years. For example, it might be the case that the return in the election year matters the most to the extent that investors overweight the most recent experience. Table 6 reports the results of our tests. Both the return in the election year (Ret_L1) and the return in the first year of the presidency (Ret_L4) have a statistically significant effect on voting. While the interaction between dividend income ratio and stock return in the second year of the presidency (Ret_L3) is not statistically significant, its magnitude is comparable to the year-one and year-four effects and its p-value is 0.125. The negative and insignificant coefficient of Ret_L2 reflects the fact during the this period, year $t-2$ return happens to have a strong negative correlation with total returns in year t-1, t-3, and t-4.

We next more formally test the null that it is the four-year total return that investors pay attention to by examining whether any individual year return has additional predictive

power above the effect of total returns. We do so by simultaneously including the interaction between dividend ratio and the four-year total return and the interaction between dividend ratio and one of single year returns. The last four columns present the results. None of the single year return interactions with the dividend ratio remains statistically significant after controlling for the total four-year return. Thus it appears that what matters for voters' decision is indeed the cumulative stock market performance since the last election.

5.3 Local vs. Market Returns

We next explore whether a county's vote is also sensitive to the return of industries or companies that the county is mostly exposed to, which we call "local returns", after controlling for aggregate stock returns. It is not clear ex ante whether and how local returns could affect voting outcome above and beyond aggregate returns. On the one hand, to the extent that investors exhibit local bias in investing or have greater exposure to local companies' stock performance for other reasons, their stock market wealth would be sensitive to local returns even controlling for overall market performance. On the other hand, if such greater exposure to local companies' stock value does not exist, to the extent that high local return is associated with better local economies, counties with high participation might be less sensitive to the performance of local industries because they have greater national exposure.

We measure local returns in two ways. First, as in Di Maggio, Kermani, Ramcharan, and Yu (2017), we calculate industry returns at the 4-digit NAICS level by the value-weighted returns of companies in each industry. We then use data from QCEW to calculate a county's employment share at the 4-digit NAICS level and calculate an employment-share-weighted industry return. Second, we measure local returns using the value-weighted return of companies headquartered in the same state. The correlation between the aggregate return and both local returns is around 0.5.

Panel B of Table 6 presents the results. Neither of the two local return interactions loads significantly after controlling for the effect of aggregate returns, while the point estimate of the aggregate return interaction remains similar in magnitude. This suggests that the performance of local companies does not differentially affect the voting behavior of people with different stock exposure.

5.4 Voter Turnout

The increase in incumbent vote share in high participation counties following good stock market performance could be due to voters switching to the incumbent party, or the incumbent party attracting voters who would have otherwise not voted at all. To distinguish these explanations, we examine the effect on voter turnout. In addition, voter turnout may be an interesting outcome variable in its own right, as it reflects citizens' political and civil engagement and affects societal welfare (Mueller and Stratmann (2003) and Krishna and Morgan (2011)).[11] The stock market's effect on turnout through economic voting channel is not clear in theory, as it has been argued that economic downturns may induce people to mobilize to participate in elections, but it may also lead them to withdraw from the political process (Rosenstone (1982) and Radcliff (1992)).

We estimate a model specification similar to Eq. (1), where the dependent variable is now the change in voter turnout, as defined in the data section. Column (1) of Table 7 shows that recent stock market performance has a negative but statistically insignificant effect on voter turnout. In column (2), when we further control for the interaction of county controls and stock return, the effect on turnout becomes smaller but statistically significant at the 10% level.[12] The evidence suggests that voter turnout in high participation counties decline slightly following good stock returns, relative to low participation counties.[13]

We next examine if stock market's effect on voter share varies with changes in voter turnout. The triple interaction term is negative but not statistically insignificant in column (3), and marginally significant in column (4) when interactions between county controls and stock returns are included in the estimation. The point estimates of the main interaction terms are similar to those reported in Table 2. Overall, while returns have a small effect on turnout, this appears to be distinct from the effect on incumbent share, suggesting that returns affect vote share mostly through the intensive margin.

[11]Examples of studies of voter turnout include Rosenstone (1982), Gentzkow (2006), Gentzkow, Shapiro, and Sinkinson (2011), and Charles and Stephens (2013).

[12]We also conduct a similar analysis as before examining potential heterogeneous effect across counties. Overall there is little evidence that the effect on turnout varies with county partisanship and ideology, or political activeness.

[13]Charles and Stephens (2013) find that higher local wages and employment lower turnout in almost all other elections but the presidential elections. The authors view their findings being consistent with information-based models of voting. Specifically, better labor market conditions raise the time costs of voters, which is much higher for local and congressional elections since the information for presidential candidates is more ubiquitous.

6 Conclusion

In this paper we study the effect of stock market performance on voting in U.S. presidential elections. We show that the stock market has an effect independent of overall economic growth on voters' assessment of the incumbent party and their votes. We establish a plausibly causal link by showing that the effect of recent stock returns on votes for the incumbent party is stronger in counties with greater stock market participation, after controlling for other county economic and demographic characteristics. The finding is consistent with at least two non-mutually exclusive interpretations. First, many voters are the so-called myopic pocketbook voters, who assign a high weight to their recent changes in personal economic conditions when assessing the performance of a president. Second, voters are not necessarily myopic or egotropic, rather they are prospective voters who judge the president by forecasted future national economic conditions, and voters with stock market exposure rely more on the stock market as an indicator.

Our study contributes to the existing literature by showing not only that financial markets are affected by politics, which is the focus of a large literature on politics and finance, but also that it could feed back into politics through votes and election outcomes, which could in turn affect the real economy through the channels emphasized in the political business cycle literature. In addition, the findings highlight the externalities of financial asset ownership on the political economy, which has received much recent attention (see, e.g., Jha (2015), Hilt and Rahn (2018), Ljungqvist et al. (2018), and Jha and Shayo (2019)).

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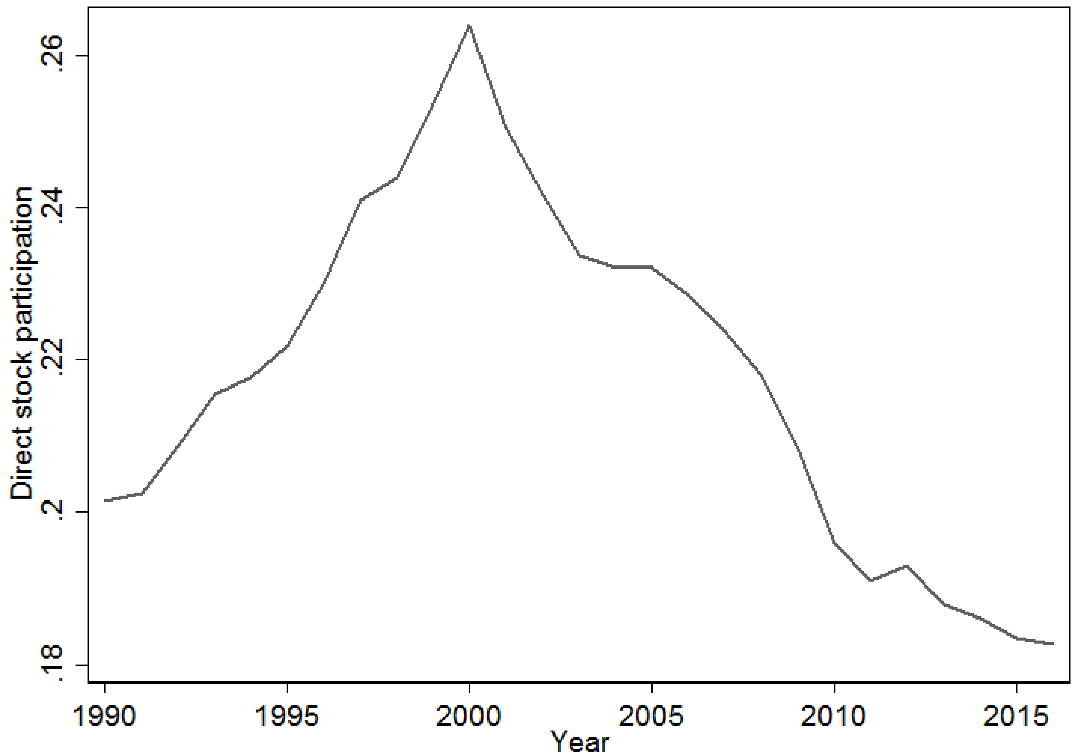
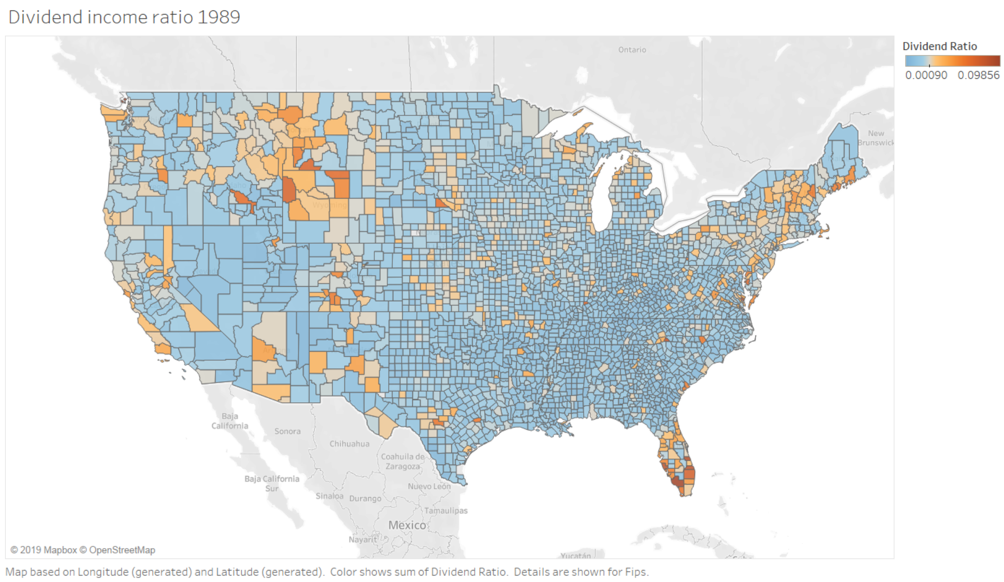
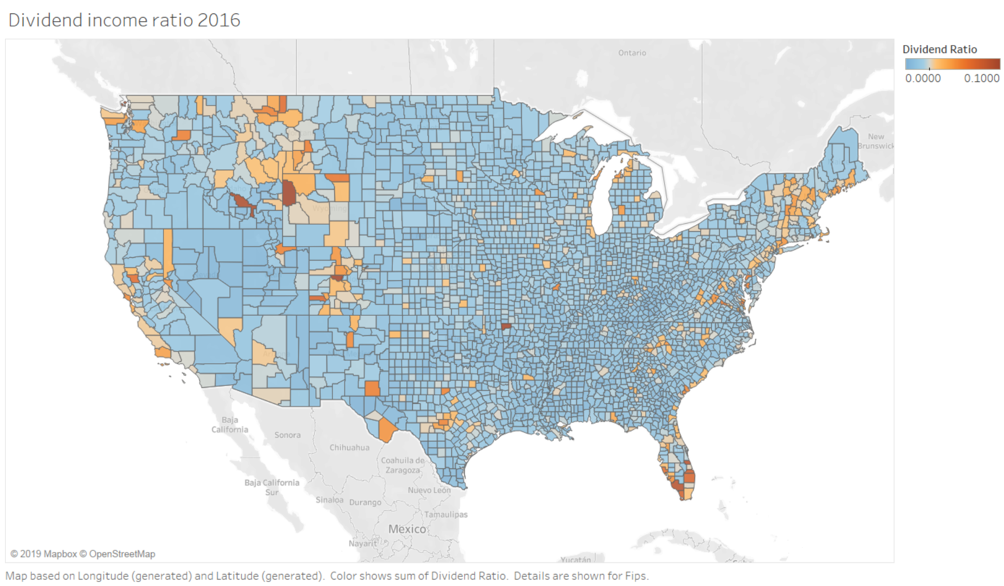


Figure 1: Stock market participation, 1990-2016. This figure plots the ratio of the number of dividend income returns over the number of total income returns. Source: IRS SOI Tax Stats.

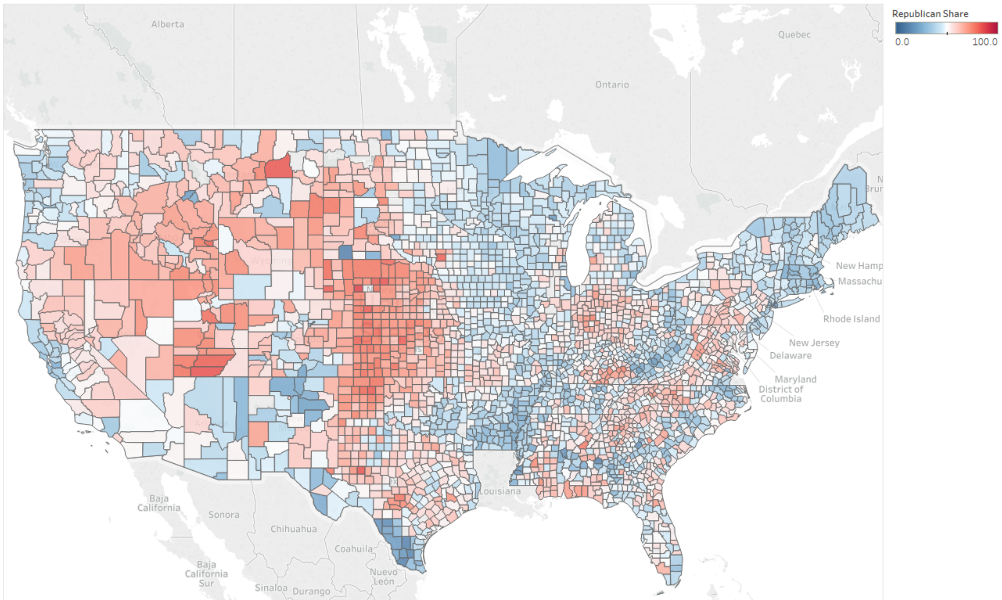


(a) 1989



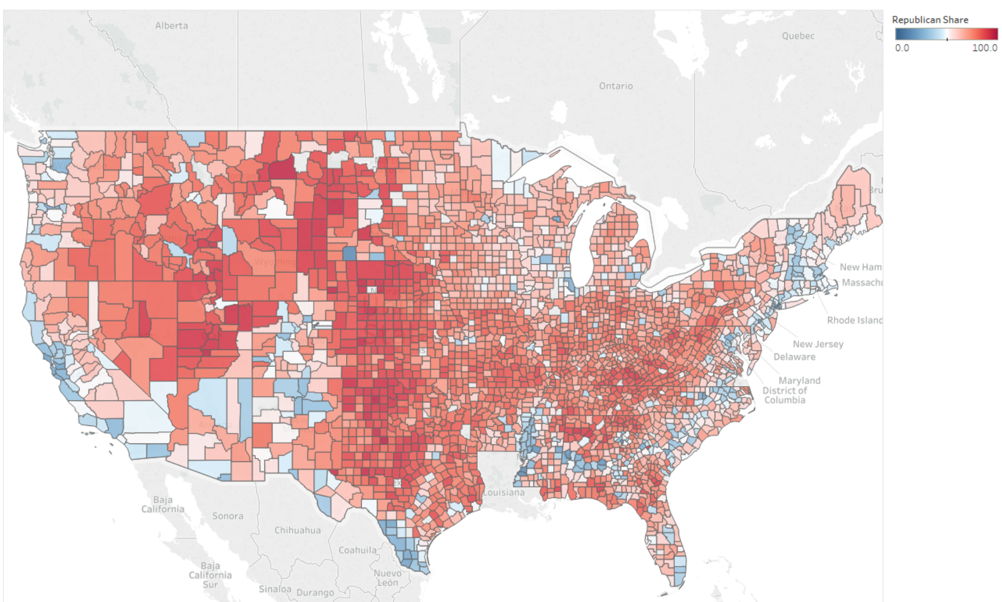
(b) 2016

Figure 2: Stock market participation. This figure shows the ratio of aggregate dividend income over aggregate taxable income for U.S. counties in 1989 and 2016.



Map based on Longitude (generated) and Latitude (generated). Color shows sum of Rep Share. Details are shown for Fips Code.

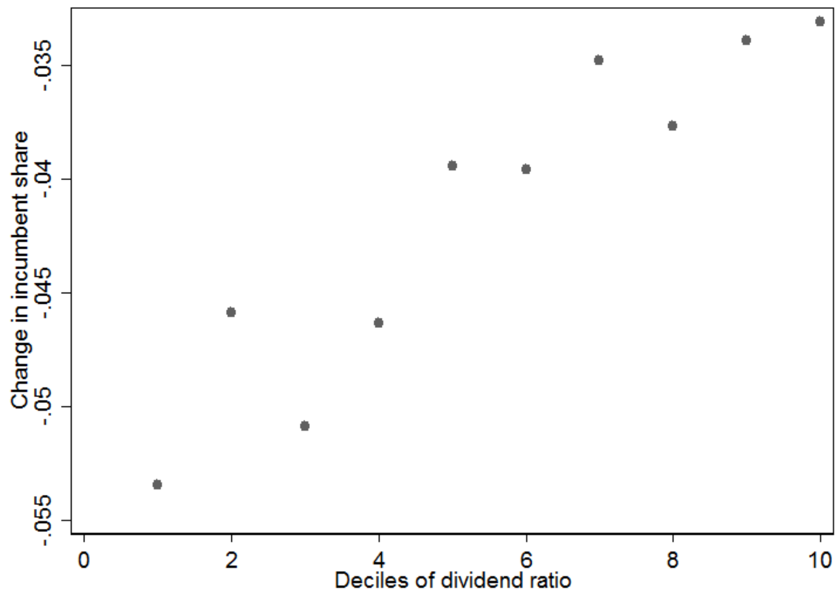
(a) 1996



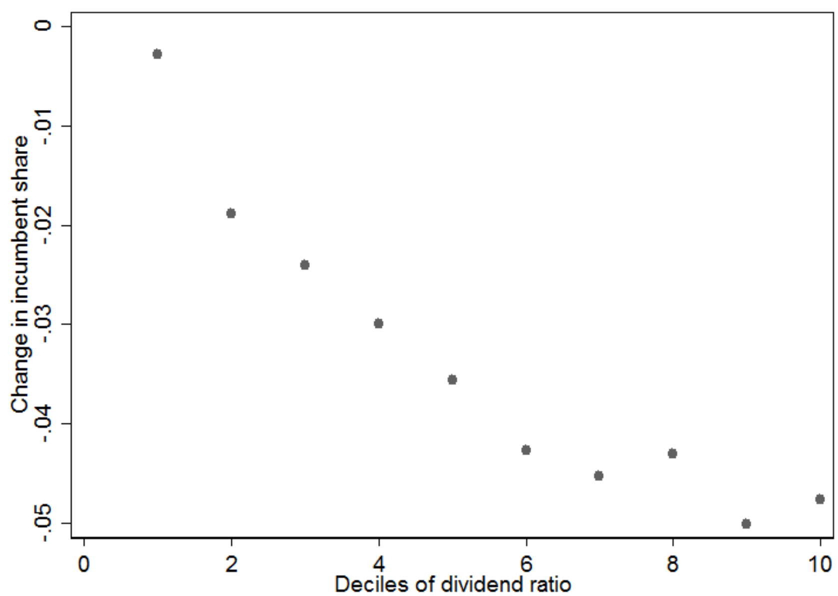
Map based on Longitude (generated) and Latitude (generated). Color shows sum of rep share (Sheet11). Details are shown for fips code (Sheet11).

(b) 2016

Figure 3: Republican vote share. The figures show the vote share for Republican candidates for U.S. counties in the 1996 and 2016 presidential elections.



(a) 2000



(b) 2008

Figure 4: This figure shows the average change in incumbent vote share by deciles of dividend income ratio for U.S. counties in 2000 and 2008.

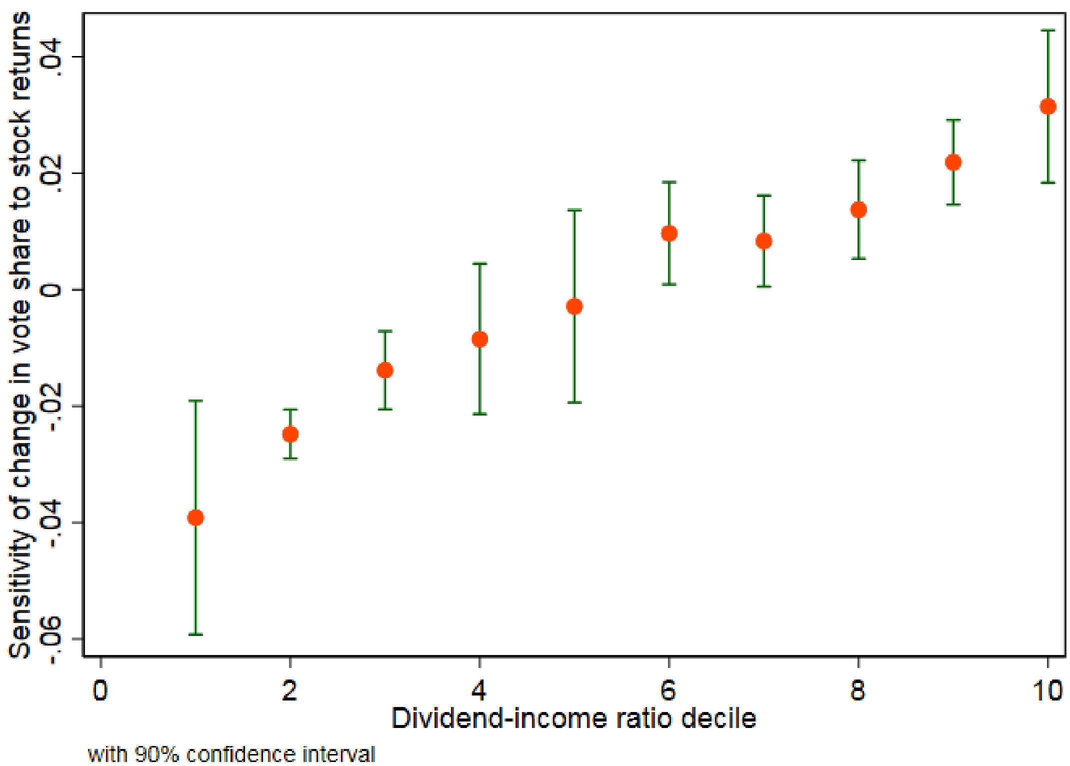


Figure 5: Sensitivity of change in incumbent vote share to stock returns by dividend income ratio decile. For counties in each decile of dividend income ratio j, we regress the change in incumbent vote share on stock return, $\Delta Incum_{ijt} = \alpha_j + \beta_j ret_t + \epsilon_{ijt}$, where i indicates county, and $\Delta Incum_{ijt}$ is demeaned by its annual average across all counties. The figure plots the estimated coefficient of stock return for each dividend income decile, as well as the 90% confidence intervals based on standard errors clustered by year.

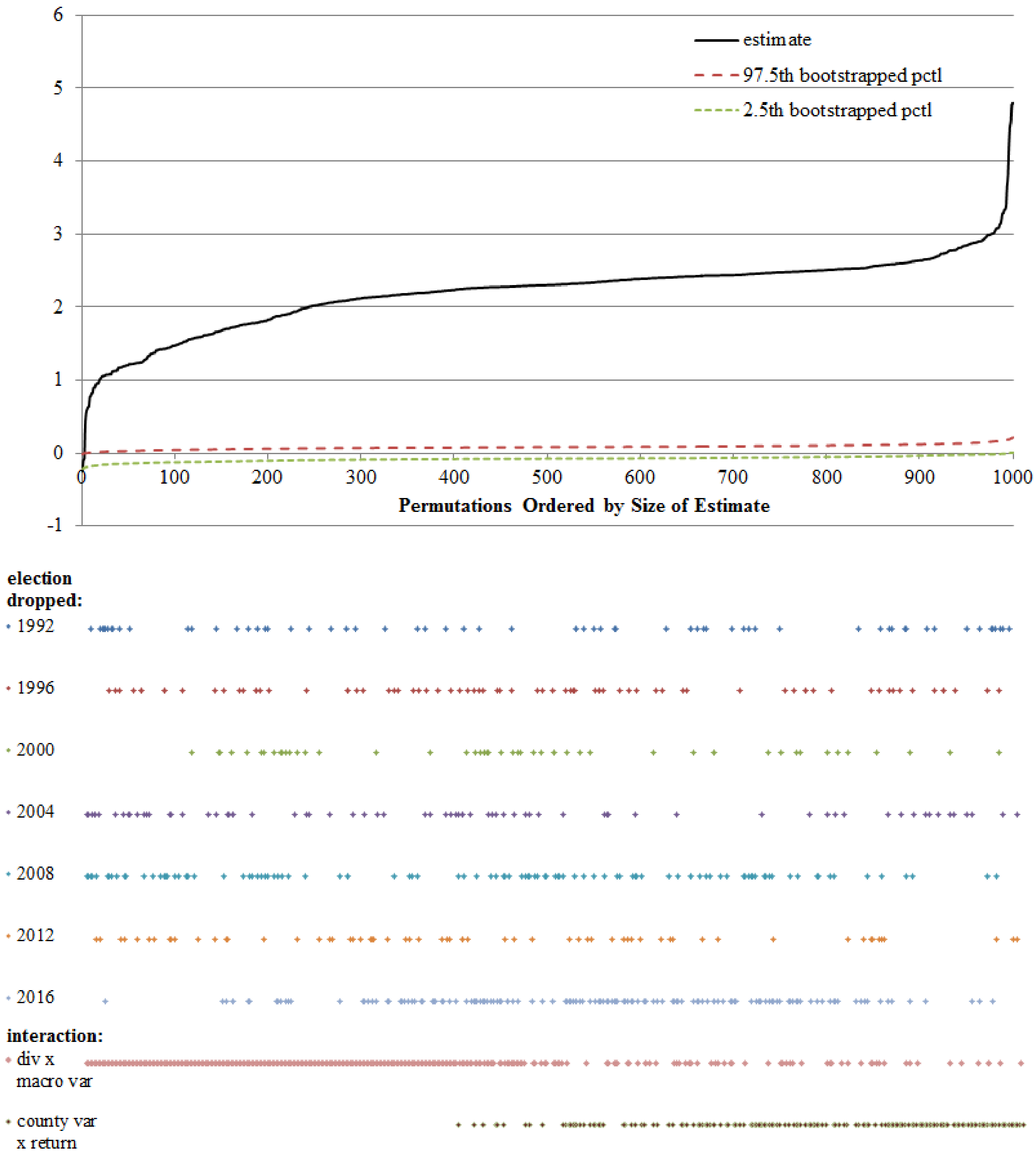


Figure 6: Specifcation Curve. The figure above plots point estimates and 95% confidence intervals of the coefficient on $Div\_ratio \times ret$ for 1,000 permutations of randomly selected regression samples and control variables. Each permutation is estimated over a random subsample of elections and counties. Controls are also selected randomly. The resulting 1,000 estimates are plotted in the solid line in order from the smallest sized effect to the largest. At the bottom we plot the characteristics of each specification.

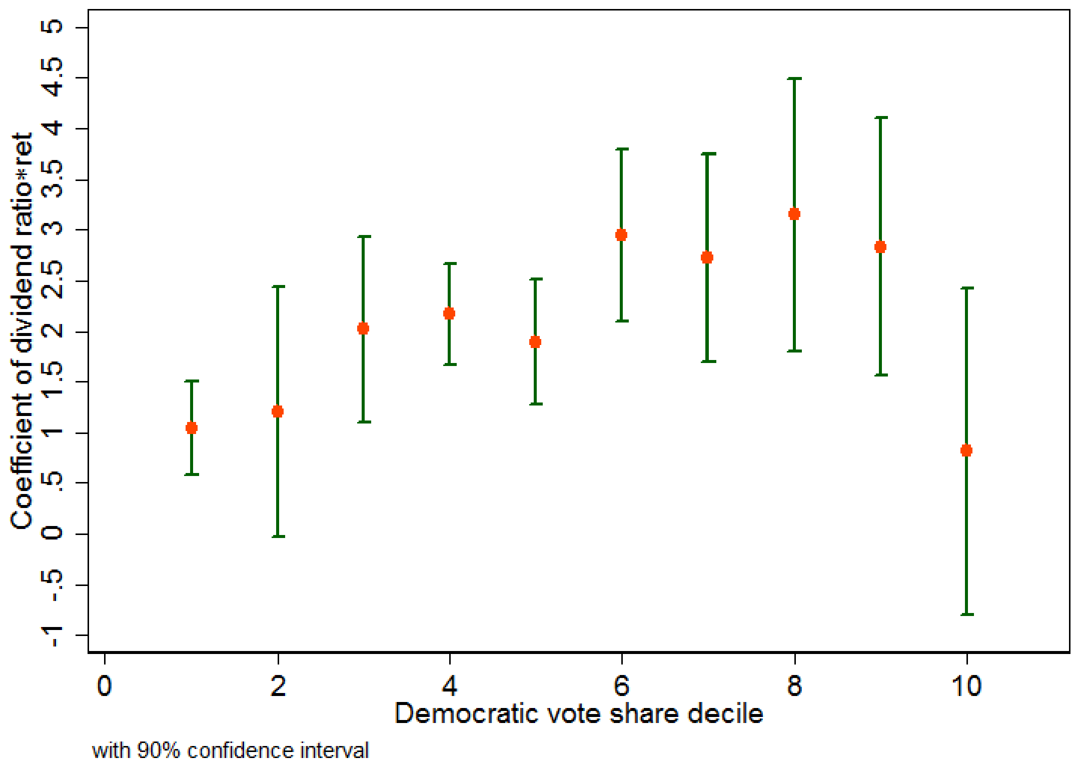


Figure 7: Point estimate of dividend ratio-return interaction by decile of Democratic share of the two-party vote. For each decile of Democratic share of the two-party vote, we estimate Eq. (1) using the same controls as in column (3) of Table 2.

Table 1: Summary statistics

In 1996, 2000, 2012, and 2016, *Incum share* is the vote share for the Democratic party, and in 1988, 1992, 2004, and 2008, *Incum share* is the vote share for the Republican party. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *Ret* is the cumulative monthly stock market return from November of the previous election year to October before the current election. *Ipc* and *Pop* are income per capita and total population from County Business Patterns. *Turnout* is the number of total votes divided by the population aged 20 or older in a county. *Wage* is the average weekly wage based on the 12-monthly employment levels and total annual wage levels from QCEW. *Unemp_rate* is the number of unemployed as a percentage of the labor force from the BLS. *White*, *Black*, and *Hispanic* are the fraction of population that is non-Hispanic White, non-Hispanic Black, and Hispanic from Census Bureau's Population Estimates Program. $Under20$ and $Over65$ are the fraction of the population that is under 20, over 65 years old, respectively. $Bachelor_{1990}$ is the fraction of population of age 25 or above with a bachelor's degree or above in 1990.

			Percentile			
	Mean	*SD*	10	50	90	*N*
Incum share	0.443	0.159	0.238	0.434	0.665	21373
Δ*Incum share*	-0.037	0.076	-0.149	-0.030	0.054	21373
Div ratio	0.016	0.009	0.007	0.015	0.027	21373
Ret	0.364	0.360	-0.189	0.466	0.858	21373
$Ln(Ipc)$	10.033	0.400	9.508	10.039	10.539	21373
$Ln(Pop)$	10.223	1.412	8.575	10.108	12.085	21373
Turnout	0.584	0.101	0.456	0.585	0.712	21366
Wage	585.1	195.2	367.0	561.0	825.0	21373
Unemp_rate	0.061	0.027	0.032	0.056	0.096	21373
White	0.808	0.191	0.527	0.884	0.979	21373
Black	0.087	0.143	0.001	0.018	0.302	21373
Hispanic	0.071	0.127	0.005	0.023	0.188	21373
$Under20$	0.273	0.037	0.229	0.272	0.316	21373
$Over65$	0.158	0.044	0.107	0.154	0.216	21373
Bachelor_1990	13.389	6.412	7.500	11.700	21.500	21373

Table 2: Stock returns and presidential election outcome

The dependent variable is the change in incumbent vote shares except for column (4) of Panel A. In 1996, 2000, 2012, and 2016, the dependent variable is the difference in vote share for the Democratic party between the last and current election, and in 1992, 2004, and 2008, the dependent variable is the difference in vote share for the Republican party between the last and current election. In column (4) of Panel A, the dependent variable is equal to 1 if the incumbent party loses the county in the previous election but wins in the current election, and -1 vice versa, and 0 otherwise. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *DemIncum* is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. *Ret* is the cumulative stock market return from November of the previous election year to October before the current election. In column (1) of Panel C, the instrument for dividend income ratio is the 1989 dividend income ratio. In column (2), the instrument is the fraction of population of age 25 or above with a bachelor's degree or above in 1990. The instruments for the interaction of dividend income ratio and stock returns are the interaction of the IV and stock returns. *Controls* and Δ*Controls* denote the level of and difference in the county economic and demographic variables shown in Panel A. Standard errors are clustered by year.

Panel A: Baseline results

	ΔIncum share			Win-lose
	(1)	(2)	(3)	(4)
$Div\_ratio \times ret$	1.41**	2.29***	2.43***	7.03***
	(0.55)	(0.30)	(0.31)	(1.25)
Div_ratio	−0.72	−0.90***	−0.82***	−2.56***
	(0.47)	(0.22)	(0.18)	(0.58)
Ret	−0.06			
	(0.05)			
ΔIpc			0.03**	0.06
			(0.01)	(0.04)
ΔPop			−0.02	−0.15
			(0.05)	(0.16)
$\Delta Wage$			−0.01	0.06
			(0.01)	(0.03)
$\Delta Unemployment$			−0.11**	0.12
			(0.04)	(0.28)
$\Delta White$			0.02	0.19
			(0.11)	(0.50)
$\Delta Hispanic$			0.01	0.04*
			(0.01)	(0.02)
$\Delta Black$			−0.07	0.23
			(0.19)	(0.39)
$\Delta Under20$			0.55**	1.75***
			(0.21)	(0.47)
$\Delta Over65$			0.03*	0.04
			(0.01)	(0.05)
Year FE	*No*	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*No*	*No*	*Yes*	*Yes*
R-squared	0.027	0.696	0.721	0.097
N	21373	21373	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Additional controls and model specifications			
	(1)	(2)	(3)
$Div\_ratio{\times}ret$	2.29***	1.68**	1.38**
	(0.57)	(0.54)	(0.39)
Div_ratio	−0.39	−0.73**	−0.38
	(0.33)	(0.26)	(0.24)
Year FE	*Yes*	*Yes*	*Yes*
ΔControls	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*
Pop weighted	*Yes*	*No*	*No*
Controls*ret	*No*	*Yes*	*No*
State*year FE	*No*	*No*	*Yes*
R-squared	0.781	0.737	0.853
N	21369	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: IV estimation		
	Div1989	Edu
$Div\_ratio{\times}ret$	1.53***	4.87**
	(0.11)	(1.53)
Div_ratio	−0.74***	−2.06**
	(0.14)	(0.80)
ΔControls	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*
State*year FE	*Yes*	*Yes*
Controls*ret	*Yes*	*Yes*
R-squared	0.864	0.854
N	21354	21362

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Stock participation and other aggregate shocks

This table reports the estimation results when controlling for dividend income ratio interacted with other aggregate shocks between elections. These aggregate shocks, indicated in the table header, include real GDP growth, real wage growth, change in unemployment rate, change in effective federal funds rates, growth in real median household income, growth in real GDP per capita, growth in real house prices, and change in credit spread. The dependent variable is the change in incumbent vote shares. In 1996, 2000, 2012, and 2016, the dependent variable is the difference in vote share for the Democratic party between the last and current election, and in 1992, 2004, and 2008, the dependent variable is the difference in vote share for the Republican party between the last and current election. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *Ret* is the cumulative stock market return from November of the previous election year to October before the current election. All regressions control for the interactions between county level controls and the aggregate variable considered in each regression. Standard errors are clustered by year.

	ΔGDP	$\Delta Wage$	$\Delta Unemp\ rate$	$\Delta FF\ rate$	$\Delta Househ\ inc$	$\Delta GDP\ per\ cap$	$\Delta House\ price$	$\Delta Cre\ spread$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Div_ratio×*ret*	2.66***	2.26***	1.34***	1.86***	1.67***	2.30**	2.47***	2.37***
	(0.61)	(0.38)	(0.13)	(0.28)	(0.42)	(0.62)	(0.51)	(0.32)
Div_ratio	−0.15	−1.02***	−0.76***	−0.70**	−0.86***	−0.64	−1.10***	−0.97***
	(0.63)	(0.13)	(0.14)	(0.24)	(0.09)	(0.43)	(0.26)	(0.19)
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
*Div_ratio**Header var	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls*Header var	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
R-squared	0.739	0.736	0.742	0.746	0.738	0.742	0.734	0.732
N	21369	21369	21369	21369	21369	21369	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Alternative measure of stock participation

The dependent variable is the change in the incumbent vote share, defined in Table 2. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *Ret* is the cumulative stock market return from November of the previous election year to October before the current election. *Participation* is the fraction of income tax returns that report dividend income in a county during the last election year. Standard errors are clustered by year.

	(1)	(2)
$Div\_ratio \times ret$		0.40
		(0.85)
$Participation \times ret$	0.44^{**}	0.41^{*}
	(0.12)	(0.18)
Div_ratio		-0.17
		(0.48)
$Participation$	-0.14^{*}	-0.13
	(0.06)	(0.09)
Year FE	Yes	Yes
ΔControls	Yes	Yes
ΔControls*DemIncum	Yes	Yes
R-squared	0.731	0.731
N	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Presidential election: heterogeneity

The dependent variable is the change in incumbent vote shares, defined in Table 2. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *Ret* is the cumulative stock market return from November of the previous election year to October before the current election. Partisan counties are those in the top and bottom decile of average Democratic share of the two-party vote. Democratic-leaning counties are those in the top half of average Democratic share of the two-party vote. Swing states include Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, Virginia, and Wisconsin. Low and high turnout counties are those with voter turnout below and above the median. Controls include (log) population, (log) income per capita, county race and age. In panel B, all double interaction terms are also controlled for but not reported. $Year * region$ denotes year fixed effects interacted with the indicator variables *partisan*, *swing*, *high_turnout*, and *dem_leaning*. Standard errors are clustered by year.

Panel A: Hetergeneity								
	Ideology				Political activeness			
	Partisan	Non-Partisan	Dem-leaning	Non-Dem-leaning	Swing	Non-swing	Low-turnout	High-turnout
$Div\_ratio \times ret$	1.58**	2.62***	2.79***	1.57***	1.55***	2.35***	2.57***	1.85***
	(0.48)	(0.38)	(0.46)	(0.26)	(0.36)	(0.41)	(0.34)	(0.33)
Div_ratio	−0.53**	−0.88***	−0.75**	−0.74***	−0.32	−0.84***	−0.86**	−0.60**
	(0.21)	(0.21)	(0.26)	(0.14)	(0.35)	(0.19)	(0.30)	(0.22)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Controls * DemIncum$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.680	0.738	0.714	0.756	0.783	0.714	0.730	0.727
N	4275	17094	10682	10687	5841	15528	10685	10684

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Test of difference		
	(1)	(2)
$Div\_ratio \times ret$	0.95^{**}	1.85^{***}
	(0.37)	(0.49)
$Div\_ratio \times ret \times partisan$	-0.29	-0.79
	(0.39)	(0.58)
$Div\_ratio \times ret \times swing$	0.37	-0.98^{*}
	(0.48)	(0.46)
$Div\_ratio \times ret \times high\_turnout$	-0.07	-0.14
	(0.33)	(0.47)
$Div\_ratio \times ret \times dem\_leaning$	1.81^{**}	1.19^{**}
	(0.61)	(0.35)
Year FE	Yes	Yes
$\Delta Controls$	Yes	Yes
$\Delta Controls * DemIncum$	Yes	Yes
$Year * Region$	No	Yes
R-squared	0.731	0.747
N	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Presidential election: timing of returns

The dependent variable is the change in incumbent vote shares, defined in Table 2. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *Ret* is the cumulative stock market return from November of the previous election year to October before the current election. *Ret_L*1 to *Ret_L*4 are the stock market return in the first to fourth year before the election, respectively. In column (1) of Panel B, local return is the county-level employment-share-weighted industry returns, where industry returns at the 4-digit NAICS level are the value-weighted returns of companies in each industry. In column (2), local return is the value-weighted return of companies headquartered in the same state. Standard errors are clustered by year.

Panel A: Timing of returns

	Return by year				Controlling for 4-year return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Div_ratio	0.14	0.31	−0.00	−0.65*	−0.75**	−0.61	−0.79**	−0.85***
	(0.37)	(0.56)	(0.34)	(0.29)	(0.24)	(0.35)	(0.22)	(0.14)
$Div\_ratio \times ret$					2.26***	2.45***	2.27***	2.08**
					(0.28)	(0.33)	(0.45)	(0.66)
$Div\_ratio \times ret\_L1$	3.61**				0.84			
	(1.06)				(0.81)			
$Div\_ratio \times ret\_L2$		−1.29				−1.47		
		(2.40)				(1.56)		
$Div\_ratio \times ret\_L3$			3.28				0.80	
			(1.81)				(1.42)	
$Div\_ratio \times ret\_L4$				4.38***				0.93
				(1.01)				(1.98)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Controls * DemIncum$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.716	0.713	0.716	0.719	0.722	0.722	0.722	0.722
N	21369	21369	21369	21369	21369	21369	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Local returns		
	County industry	State headquarter
$Div\_ratio \times ret$	2.50^{***}	2.32^{***}
	(0.39)	(0.40)
Div_ratio	-0.84^{**}	-0.88^{***}
	(0.25)	(0.23)
$Div\_ratio \times local\ ret$	-0.02	0.20
	(0.12)	(0.21)
$Local\ ret$	0.00	-0.00
	(0.00)	(0.00)
Year FE	Yes	Yes
ΔControls	Yes	Yes
ΔControls*DemIncum	Yes	Yes
R-squared	0.714	0.722
N	19987	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Turnout

The dependent variable is the change in voter turnout in the first two columns, defined as the number of total votes dividend by the population aged 20 or older in a county. The dependent variable is the change in incumbent vote share, in columns (3) and (4). *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *Ret* is the cumulative stock market return from November of the previous election year to October before the current election. Controls include (log) population, (log) income per capita, county race and age. Standard errors are clustered by year.

	Turnout		Incumbent vote share	
	(1)	(2)	(3)	(4)
$Div\_ratio \times ret$	−0.64	−0.48*	2.39***	1.74**
	(0.34)	(0.24)	(0.31)	(0.52)
Div_ratio	0.30	0.15	−0.83**	−0.81**
	(0.20)	(0.12)	(0.24)	(0.30)
$Div\_ratio \times ret \times \Delta turnout$			−9.36	−11.49*
			(5.24)	(4.80)
$Div\_ratio \times \Delta turnout$			2.58	3.25
			(2.90)	(2.68)
$ret \times \Delta turnout$			0.51***	0.48**
			(0.12)	(0.14)
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*	*Yes*
Controls*ret	*No*	*Yes*	*No*	*Yes*
R-squared	0.551	0.564	0.728	0.742
N	21369	21369	21369	21369

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDICES

Table A.I: Determinants of stock market participation

The dependent variable is the dividend income ratio, measured in percentage points. *Ipc* and *Pop* are income per capita and total population. *White*, *Black*, and *Hispanic* are the fraction of population that is non-Hispanic White, non-Hispanic Black, and Hispanic from Census Bureau's Population Estimates Program. *Under*20 and *Over*65 are the fraction of the population that is under 20, over 65 years old, respectively. $Bachelor_{1990}$ is the fraction of population of age 25 or above with a bachelor's degree or above in 1990.

	(1)	(2)	(3)	(4)
Div_ratio_{1989}	0.611***	0.611***		
	(0.029)	(0.029)		
$Ln(Ipc)$			1.765***	0.790***
			(0.048)	(0.052)
$Ln(Pop)$			0.042	0.008
			(0.040)	(0.028)
$White$			−1.156***	−0.348**
			(0.138)	(0.126)
$Hispanic$			−0.322**	0.147
			(0.098)	(0.103)
$Black$			−0.782***	−0.002
			(0.163)	(0.142)
$Under20$			−4.901***	−2.310***
			(0.429)	(0.451)
$Over65$			5.998***	8.723***
			(0.288)	(0.347)
$Bachelor_{1990}$				0.060***
				(0.003)
Year FE	No	Yes	Yes	Yes
R-squared	0.498	0.510	0.349	0.439
N	21365	21365	21373	21373

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$